

Modern Spectral Estimation Theory And Application Updated Version

Modern spectral estimation theory and application

Spectral estimation theory is a cornerstone of signal processing, focusing on analyzing the frequency content of signals. Over the years, advancements in modern spectral estimation have significantly enhanced our ability to accurately identify and interpret spectral components in complex signals. These techniques are crucial across diverse fields such as telecommunications, radar, audio engineering, biomedical signal analysis, and geophysics. This comprehensive overview explores the foundations, developments, and practical applications of modern spectral estimation, offering insights into both theoretical frameworks and real-world implementations.

Fundamentals of Spectral Estimation

Spectral estimation involves determining the power distribution of a signal over frequency. Unlike classical methods like the periodogram, which often suffer from bias and variance issues, modern techniques aim to provide higher resolution and more reliable estimates, particularly with limited data.

Basic Concepts and Definitions

- **Power Spectral Density (PSD):** Describes how the power of a signal is distributed with frequency.
- **Autocorrelation Function:** Measures the similarity of a signal with a delayed version of itself, serving as a basis for spectral analysis.
- **Spectral Resolution:** The ability to distinguish between closely spaced frequency components.

Limitations of Classical Methods

- **Periodogram:** Simple but suffers from high variance and spectral leakage.
- **Windowing Techniques:** Reduce leakage but at the cost of resolution.

Advancements in Spectral Estimation Techniques

Modern spectral estimation methods address classical limitations through sophisticated algorithms,

statistical modeling, and computational techniques.

Parametric Spectral Estimation Methods

Parametric methods assume the signal can be modeled as an output of a known system with unknown parameters.

- **AR (Autoregressive) Models:** These models assume the current value of the signal depends on previous values plus noise. They are especially effective for narrowband signals.
- **MA (Moving Average) and ARMA Models:** Combine autoregressive and moving average models for more flexible representations.
- **Advantages:** High resolution with limited data, ability to model spectral peaks precisely.

Non-Parametric Spectral Estimation Techniques

These do not assume a specific model for the signal but rely on data-driven approaches.

- **Multitaper Method:** Utilizes multiple orthogonal tapers to reduce variance and spectral leakage.
- **Spectral Smoothing:** Applies smoothing kernels to stabilize estimates.
- **Advantages:** Robustness to noise and versatility across different signal types.

Modern Algorithms and Approaches

Recent innovations have combined classical and modern concepts:

- **Maximum Entropy Method (MEM):** Seeks the spectral estimate with maximum entropy consistent with the data, resulting in high resolution.
- **Subspace Methods (e.g., MUSIC and ESPRIT):** Exploit signal subspace properties to detect multiple spectral components with high resolution, ideal for closely spaced signals.
- **Time-Frequency Analysis (Wavelets, Wigner-Ville):** Provides localized spectral information, useful for non-stationary signals.

Applications of Modern Spectral Estimation

The practical utility of modern spectral estimation spans various domains, enabling better signal analysis, system identification, and feature extraction.

Telecommunications

- **Spectrum Monitoring:** Detecting spectral occupancy and interference for cognitive radio systems.
- **Channel Estimation:** Identifying frequency response characteristics for adaptive communication systems.
- **Signal Detection:** Recognizing narrowband signals amidst noise using high-resolution methods like MUSIC.

Radar and Sonar Systems

- **Target Detection:** Resolving multiple targets with similar Doppler shifts.
- **Clutter Suppression:** Differentiating between moving objects and background noise.
- **Velocity Estimation:** Precise Doppler frequency estimation for speed measurement.

Biomedical Signal Analysis

- **EEG and ECG Analysis:** Identifying spectral features associated with neurological or cardiac conditions.
- **Sleep Studies:** Analyzing brain wave patterns to diagnose sleep disorders.
- **Neural Oscillations:** Studying brain rhythms related to cognitive functions.

Geophysics and Earth Sciences

- **Seismic Data Analysis:** Detecting underground structures and events.
- **Environmental Monitoring:** Analyzing temporal variations in geophysical signals.
- **Climate Modeling:** Spectral analysis of climate data for periodicity detection.

Challenges and Future Directions

Despite significant progress, spectral estimation faces ongoing challenges:

- **Limited Data Length:** Short data records can limit resolution, especially for parametric methods.
- **Non-Stationarity:** Many signals vary over time, requiring adaptive and time-frequency methods.
- **Computational Complexity:** High-resolution algorithms like MUSIC and ESPRIT can be computationally intensive.
- **Noise and Interference:** Improving robustness remains a key focus.

Future research directions include:

- **Machine Learning Integration:** Leveraging AI for adaptive spectral estimation and pattern recognition.
- **Real-Time Processing:** Developing algorithms optimized for low-latency applications.
- **Multidimensional Spectral Analysis:** Extending techniques to spatiotemporal data.
- **Hybrid Methods:** Combining parametric, non-parametric, and data-driven approaches for enhanced performance.

Conclusion

Modern spectral estimation theory has evolved into a sophisticated toolkit that significantly improves our capability to analyze complex signals across numerous fields. From high-resolution parametric methods to adaptive time-frequency approaches, these techniques enable precise, reliable, and insightful spectral analysis even under challenging conditions. As technology advances, ongoing innovations promise to further enhance spectral estimation's role in scientific research, engineering, and beyond, making it an indispensable component of modern signal processing.

Keywords: spectral estimation, power spectral density, parametric methods, non-parametric methods, MUSIC, ESPRIT, multitaper, signal processing, high-resolution spectral analysis, time-frequency analysis

Spectral Estimation Theory and Its Applications: A Comprehensive Review

Spectral estimation is a fundamental aspect of signal processing, providing critical insights into the frequency content of signals. As modern systems increasingly rely on accurate frequency analysis—ranging from telecommunications and radar to biomedical engineering and financial modeling—the evolution of spectral estimation theory has become vital. This review delves into the core principles, methodologies, and applications of modern spectral estimation, highlighting both classical techniques and recent advancements.

Introduction to Spectral Estimation

Spectral estimation involves determining the power distribution of a signal over frequency. Unlike simple Fourier analysis, which provides a frequency spectrum based on finite data, spectral estimation aims to infer the underlying spectral characteristics, often from limited or noisy data. This process is essential for understanding signal behavior, filtering, detection, and system identification.

Key motivations include:

- Identifying dominant frequencies or harmonics.
- Detecting periodicities in noisy environments.
- Estimating spectral density for system modeling.
- Enhancing resolution beyond traditional Fourier methods.

Classical vs. Modern Spectral Estimation

While classical methods like periodograms and Bartlett's estimators laid the groundwork, they often suffer from limitations such as spectral leakage, poor resolution, and high variance. Modern spectral estimation techniques seek to overcome these challenges through more sophisticated algorithms, leveraging statistical models, optimization, and computational advancements.

Classical Techniques:

- Periodogram: The squared magnitude of the Fourier transform; simple but has high variance.
- Bartlett's Method: Averages periodograms from segmented data to reduce variance.
- Welch's Method: Improves Bartlett's by windowing and overlapping segments.
- Blackman-Tukey: Uses autocorrelation estimates and windowing for smoothing.

Modern Techniques:

- Parametric methods (e.g., autoregressive (AR), moving average (MA), ARMA models).
- Subspace methods (e.g., MUSIC, ESPRIT).
- Compressive sensing approaches.
- Bayesian spectral estimation.

Fundamentals of Modern Spectral Estimation

Modern spectral estimation hinges on the idea that signals can be modeled using parametric or non-parametric frameworks. These approaches incorporate statistical models, optimization, and prior information to produce high-resolution spectral estimates.

Parametric Methods

Parametric methods assume the signal is generated by a finite number of sinusoidal components plus noise. They estimate model parameters and derive the spectrum from these.

Key techniques include:

- Autoregressive (AR) modeling: Assumes the signal satisfies an AR process; the spectrum is derived from the AR coefficients.
- Moving Average (MA) and ARMA models: More flexible models combining AR and MA components.

Advantages:

- High resolution with fewer data samples.
- Ability to resolve closely spaced frequencies.

Limitations:

- Requires model order selection.
- Sensitive to model assumptions and noise.

Subspace Methods

Subspace methods exploit the structure of the data's autocorrelation matrix to distinguish between signal and noise subspaces, providing high-resolution spectral estimates.

Prominent algorithms:

- MUSIC (Multiple Signal Classification): Estimates frequencies by searching for peaks orthogonal to the noise subspace.
- ESPRIT (Estimation of Signal Parameters via Rotational Invariance Techniques): Uses invariance properties for parameter estimation.

Strengths:

- Excellent resolution for closely spaced signals.
- Can estimate the number of sources/signals.

Challenges:

- Sensitive to model order estimation.
- Requires sufficiently long data records.

Advancements in Spectral Estimation

Recent developments have expanded the capabilities and robustness of spectral estimation methods.

Compressive Sensing

Leveraging sparsity in the frequency domain, compressive sensing (CS) enables reconstruction of signals from fewer samples than traditional Nyquist sampling would require. CS-based spectral estimation is particularly useful in applications where data acquisition is costly or constrained.

Key features:

- Exploits signal sparsity.
- Provides super-resolution estimates.
- Suitable for wideband signals with sparse spectra.

Bayesian Spectral Estimation

Bayesian methods incorporate prior information and probabilistic models, providing a framework for uncertainty quantification and robustness in noisy environments.

Approaches include:

- Bayesian AR modeling.
- Hierarchical models for spectral estimation.
- Markov Chain Monte Carlo (MCMC) algorithms for inference.

Advantages:

- Incorporates prior knowledge.
- Produces confidence intervals for spectral estimates.

Machine Learning and Data-Driven Techniques

Recent trends involve using deep learning to perform spectral estimation, especially in complex or non-stationary scenarios.

Examples:

- Neural networks trained to identify spectral features.
- Recurrent neural networks modeling temporal dynamics.
- Data-driven models that adapt to changing signal characteristics.

Applications of Modern Spectral Estimation

The versatility of spectral estimation techniques allows their application across numerous fields. Here, we explore some prominent domains.

Communications and Radar

- Spectrum sensing: Identifying occupied frequency bands in cognitive radio.
- Target detection: Estimating Doppler shifts in radar signals.
- Channel estimation: Inferring multipath components and their delays.

Biomedical Signal Processing

- Electroencephalogram (EEG) analysis: Identifying brain rhythms (alpha, beta, gamma).
- Electrocardiogram (ECG): Detecting heart rate variability.
- Speech processing: Enhancing speech signals and extracting features.

Seismology and Geophysics

- Detecting seismic events.
- Estimating earth's subsurface properties through spectral content.
- Monitoring volcanic activity via spectral signatures.

Financial Data Analysis

- Identifying periodicities or cycles in stock prices.
- Modeling volatility and market dynamics.
- Detecting regime shifts.

Environmental and Climate Studies

- Analyzing climate variability.
- Monitoring ocean wave spectra.
- Remote sensing applications.

Challenges and Future Directions

Despite significant progress, spectral estimation faces ongoing challenges:

- Handling Non-Stationarity: Many real-world signals are non-stationary, requiring adaptive or time-frequency methods.
- Model Order Selection: Accurate estimation depends on choosing the right model complexity.
- Computational Efficiency: High-resolution methods can be computationally intensive.
- Robustness to Noise: Ensuring reliable estimates in noisy environments.

Future research directions include:

- Developing real-time adaptive algorithms.
- Integrating machine learning for model selection and enhancement.
- Exploring quantum-based spectral estimation.
- Combining spectral estimation with other modeling approaches like deep learning.

Conclusion

Modern spectral estimation theory represents a rich, evolving field that combines statistical modeling, signal processing, and computational techniques to achieve high-resolution, robust frequency analysis. Its applications are broad, spanning communications, biomedical sciences, geophysics, finance, and beyond. As technological demands grow and data become more complex, the continued development of spectral estimation methods—particularly those leveraging sparsity, Bayesian inference, and machine learning—will be essential in extracting meaningful spectral insights from an ever-increasing variety of signals.

By understanding both classical foundations and cutting-edge innovations, practitioners and researchers can better harness spectral estimation techniques to solve real-world problems, improve system performance, and unlock new scientific discoveries.

Question What are the key advancements in modern spectral estimation theory compared to classical methods? Modern spectral estimation incorporates advanced algorithms like high-resolution parametric methods (e.g., MUSIC, ESPRIT), Bayesian approaches, and machine learning techniques, enabling higher frequency resolution, better noise robustness, and the ability to

handle limited or noisy data more effectively than traditional methods like periodogram or Welch. How are modern spectral estimation techniques applied in radar and sonar signal processing? In radar and sonar, modern spectral estimation techniques are used for accurate target detection, velocity estimation, and clutter suppression by providing high-resolution spectral analysis, even with limited data samples, which enhances detection capabilities in complex and noisy environments. What role does Bayesian spectral estimation play in analyzing non-stationary signals? Bayesian spectral estimation models the spectral content probabilistically, allowing for adaptive and robust analysis of non-stationary signals by incorporating prior information, which improves spectral estimates in the presence of noise and signal variability. How does compressed sensing influence modern spectral estimation, and what are its practical applications? Compressed sensing enables the reconstruction of sparse spectral signals from limited measurements, reducing data acquisition requirements. It is widely used in applications like biomedical imaging, wireless communications, and spectrum sensing, where data collection is costly or constrained. What are the challenges and future directions in applying modern spectral estimation theory to real-world problems? Challenges include computational complexity, model order selection, and robustness to model mismatches. Future directions focus on integrating machine learning for adaptive estimation, real-time processing capabilities, and extending methods to multidimensional and non-stationary signal analysis for diverse applications.

Related keywords: spectral analysis, signal processing, Fourier transform, power spectral density, time series analysis, frequency domain analysis, adaptive filtering, windowing techniques, spectral estimation algorithms, applications in communications

An introduction to ergodic theory graduate texts i

An introduction to ergodic theory graduate texts i serves as a foundational guide for graduate students venturing into this fascinating branch of mathematics. Ergodic theory, at its core, explores the long-term average behavior of dynamical systems and their statistical properties. It has profound applications across mathematics, physics, and even in fields like economics and computer science. For students beginning their journey, selecting the right graduate texts is crucial for building a solid understanding, developing intuition, and engaging with current research directions. This article aims to provide a comprehensive overview of essential ergodic theory texts, their key features, and how they can serve as effective learning tools.

Understanding the Foundations of Ergodic Theory

Before diving into specific texts, it's important to understand what ergodic theory encompasses and why it's a vital area of study. This section offers a brief overview of the fundamental concepts and

the scope of graduate-level texts.

What is Ergodic Theory?

Ergodic theory studies the behavior of measure-preserving transformations on probability spaces. Essentially, it addresses questions like: How do points in a dynamical system distribute over time? Do the time averages of functions along trajectories converge to space averages? These questions are rooted in the ergodic hypothesis, which originated from statistical mechanics.

Key concepts include:

- Measure-preserving transformations
- Ergodicity and mixing
- Invariant measures
- Birkhoff's Ergodic Theorem
- Unique ergodicity

Understanding these ideas lays the groundwork for exploring more advanced topics covered in graduate texts.

Essential Graduate Texts in Ergodic Theory

Choosing the right textbooks is essential for mastering ergodic theory. The following sections highlight some of the most influential and widely recommended graduate-level texts, discussing their strengths and targeted audiences.

1. "An Introduction to Ergodic Theory" by Peter Walters

Walters' book is often considered a classic starting point for graduate students.

Key features:

- Clear and rigorous presentation
- Focuses on measure-theoretic foundations
- Covers fundamental theorems such as Birkhoff's and von Neumann's
- Includes numerous exercises for practice

This text is ideal for students new to the field, providing a solid theoretical foundation before moving to more specialized topics.

2. "Ergodic Theory" by Karl Petersen

Petersen's work is comprehensive and slightly more advanced.

Key features:

- Emphasizes both measure-theoretic and topological dynamics
- Discusses entropy, mixing, and applications
- Contains detailed proofs and examples
- Suitable for students with some background in measure theory and topology

This book bridges foundational concepts with more recent developments, making it a good next step after Walters.

3. "Introduction to Ergodic Theory" by Ya. G. Sinai

Sinai's text offers a blend of intuition and formalism.

Key features:

- Focuses on the intuition behind the theorems
- Connects ergodic theory with statistical mechanics
- Includes historical notes and motivations
- Suitable for students who prefer a conceptual approach

Additional Resources and Advanced Texts

Graduate students aiming to deepen their understanding should explore more specialized and advanced texts. Here are some noteworthy options:

1. "Ergodic Theory and Differentiable Dynamics" by Anatole Katok and Boris Hasselblatt

This comprehensive volume covers a broad spectrum of topics.

Highlights:

- Smooth ergodic theory

- Hyperbolic systems and Anosov diffeomorphisms
- Structural stability
- It is suitable for students interested in the interface between ergodic theory and differential dynamics.

2. "Measure Theory and Probability" by Malcolm Adams and Victor Guillemin

While broader in scope, this book provides valuable measure-theoretic background essential for advanced ergodic theory.

Strategies for Studying Ergodic Theory Graduate Texts

Mastering ergodic theory requires more than just reading; active engagement is key. Here are some tips for making the most of these texts:

- **Start with the basics:** Ensure a solid understanding of measure theory, topology, and functional analysis.
- **Work through exercises:** Practice problems reinforce concepts and develop problem-solving skills.
- **Supplement with lectures and seminars:** Engage with online courses or university seminars for different perspectives.
- **Form study groups:** Discussing complex topics with peers enhances understanding.
- **Connect theory to applications:** Explore how ergodic theory applies to physics, information theory, and other fields.

Conclusion

An introduction to ergodic theory graduate texts provides a roadmap for students embarking on this mathematical journey. Starting with foundational books like Walters' "An Introduction to Ergodic Theory" offers an accessible entry point, while advanced texts like Katok and Hasselblatt's work open doors to current research areas. By selecting appropriate resources, actively engaging with the material, and connecting theory with applications, students can develop a deep and lasting understanding of ergodic theory. Whether your interest lies in pure mathematics, statistical mechanics, or dynamical systems, the right graduate texts are invaluable tools for your academic and research pursuits in ergodic theory.

An Introduction to Ergodic Theory Graduate Texts: A Comprehensive Guide for Students and Enthusiasts

Embarking on the study of ergodic theory graduate texts opens a gateway to a rich and profound

branch of mathematics that intersects dynamical systems, measure theory, probability, and statistical mechanics. For graduate students venturing into this field, selecting the right textbooks can significantly influence their understanding and appreciation of the subject. This guide aims to shed light on the foundational texts, their structure, strengths, and how they serve as stepping stones into the depths of ergodic theory.

Understanding the Foundations of Ergodic Theory

Before diving into specific texts, it's crucial to grasp what ergodic theory entails. At its core, ergodic theory studies the long-term average behavior of dynamical systems with an invariant measure. Its applications range from statistical physics and information theory to number theory and chaos theory.

Key concepts include:

- Measure-preserving transformations
- Invariant measures
- Ergodicity and mixing
- Birkhoff's Ergodic Theorem
- Ornstein's theory of Bernoulli flows

Graduate texts in ergodic theory typically assume familiarity with measure theory, topology, and basic dynamical systems, making it a challenging yet rewarding subject for advanced students.

The Landscape of Graduate Texts in Ergodic Theory

Choosing a graduate-level textbook involves understanding its approach, prerequisites, and depth. The major texts in the field can generally be categorized based on their focus: foundational theory, applications, or a blend of both.

Classic and Seminal Texts

- "Ergodic Theory" by Peter Walters
 - Overview: Widely regarded as a definitive introductory textbook, Walters' "Ergodic Theory" is praised for clarity, rigorous proofs, and comprehensive coverage.
 - Scope: It covers measure-preserving transformations, ergodic decomposition, mixing properties, and entropy.

- Strengths:
- Well-structured for graduate courses
- Emphasizes the connection between measure theory and dynamics
- Includes numerous examples and exercises
- Prerequisites: Measure theory, basic topology, and some familiarity with dynamical systems.

- "An Introduction to Ergodic Theory" by Peter Walters

- Often considered the go-to text for graduate students or advanced undergraduates beginning the subject.
- Focuses on core concepts with detailed proofs.
- Suitable as a primary textbook or supplementary resource.

Advanced and Specialized Texts

- "Ergodic Theory via Joinings" by Eli Glasner

- Overview: Focuses on joinings, a sophisticated tool in ergodic theory, providing a modern perspective.
- Audience: More suitable for students who have already mastered the basics and want to explore advanced topics.
- Features: Incorporates recent developments, emphasizing the structural and classification aspects of ergodic systems.

- "Entropy, Large Deviations, and Statistical Mechanics" by David Ruelle

- While broader in scope, this text delves into the thermodynamic formalism? a key area in ergodic theory.
- Ideal for students interested in the applications of ergodic theory in statistical physics.

Textbooks with a Focus on Applications or Interdisciplinary Approaches

- "Ergodic Theory: with a view towards Number Theory" by Manfred Einsiedler and Thomas Ward

- Overview: Connects ergodic theory with number theory, providing applications to problems like equidistribution and primes.
- Features: Combines rigorous theory with motivating applications, making it accessible and engaging.

How to Choose the Right Graduate Text in Ergodic Theory

When selecting a textbook, consider the following factors:

- Prerequisites: Ensure you have a solid background in measure theory and topology.
- Focus Area: Decide whether you want a foundational understanding or a focus on particular applications.
- Depth: Some texts offer a broad overview, while others delve into specialized topics.
- Teaching Style: Supplementary materials, exercises, and clarity of exposition can greatly impact your learning.

Recommended approach:

- Start with Walters' "Ergodic Theory" for a comprehensive foundation.
- Use other texts, like Glasner's "Ergodic Theory via Joinings," for advanced topics.
- Supplement with research papers and lecture notes for recent developments.

Structuring Your Study of Ergodic Theory

To maximize your understanding, consider a structured approach:

- Build a Strong Measure Theory Foundation
 - Review measure spaces, sigma-algebras, and integration.
 - Study probability theory basics, as ergodic theory often involves probabilistic concepts.
- Understand Dynamical Systems
 - Familiarize yourself with topological and measurable dynamics.
 - Explore examples like rotations, shifts, and hyperbolic systems.

- Dive into Core Ergodic Concepts
 - Invariant measures and ergodicity
 - Birkhoff's Ergodic Theorem
 - Mixing properties and their implications
- Explore Advanced Topics
 - Entropy theory
 - Ornstein's isomorphism theorem
 - Joinings and structural classification
 - Connections with number theory and statistical mechanics

Supplementary Resources and Learning Strategies

- Lecture series: Many universities offer free lecture notes; for example, the lecture series by Peter Walters or others available online.
- Problem sets: Practice through exercises in textbooks or problem books.
- Research papers: Engage with current developments by reading papers in journals like Ergodic Theory and Dynamical Systems.
- Discussion groups: Join seminars or study groups focused on ergodic theory.

Conclusion

An introduction to ergodic theory graduate texts is essential for anyone aiming to master the subject at an advanced level. The journey begins with foundational texts like Peter Walters' "Ergodic Theory," which offers clarity and depth, and then progresses into more specialized or application-driven materials. By understanding the structure, prerequisites, and scope of these texts, students can tailor their learning path effectively. With dedication, rigorous study, and engagement with supplementary materials, mastering ergodic theory becomes an achievable and intellectually rewarding pursuit.

Final Tips

- Be patient: The subject is challenging but immensely rewarding.
- Connect theory with examples: Visualize systems like rotations or shifts.

- Engage actively: Solve problems and participate in discussions.
- Keep abreast of current research: This enriches your understanding and opens new avenues.

Embark on this mathematical voyage with confidence?ergodic theory offers profound insights into the behavior of complex systems and the nature of randomness and order in mathematics.

Question What is the primary focus of 'An Introduction to Ergodic Theory' by Peter Walters? The book provides a rigorous introduction to ergodic theory, focusing on measure-preserving transformations, ergodic theorems, and their applications in dynamical systems and statistical mechanics. Which prerequisites are recommended before studying this text? A solid background in measure theory, real analysis, and basic topology is recommended to fully grasp the concepts presented in the book. How does the book approach the topic of ergodic theorems? It systematically introduces the mean and pointwise ergodic theorems, providing proofs and discussing their implications in the context of dynamical systems. Are there applications of ergodic theory discussed in this graduate text? Yes, the book explores applications such as statistical properties of dynamical systems, mixing, and entropy, illustrating how ergodic theory connects to various fields. Is this book suitable for self-study or primarily for classroom use? While designed as a graduate textbook, it is also suitable for self-study due to its clear explanations, though some background in measure theory is helpful. What makes 'An Introduction to Ergodic Theory' by Walters a trending choice among graduate texts? Its comprehensive coverage, clear exposition, and balance between theory and applications have made it a popular and influential resource in the field of ergodic theory.

Related keywords: ergodic theory, measure theory, dynamical systems, invariant measures, ergodicity, mixing, entropy, Birkhoff's theorem, stationary processes, ergodic decomposition

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